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RadarSLAM: Biomimetic SLAM using Ultra-Wideband Pulse-Echo Radar

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***Abstract*—This paper presents a novel method for using an ultra-wideband (UWB), super high frequency (SHF) pulse-echo radar sensor as a biomimetic sensing mechanism to successfully solve the Simultaneous Localization and Mapping (SLAM) problem. Due to recent advances in consumer radar technology it has become possible to sample the received echo signals well above their Nyquist frequency. This Nyquist-conform sampling permits the conversion of the signal waveforms into spectrograms which contain spatiospectral cues caused by the interactions of the echoes with features of the environment and the antenna's radiation pattern. Such spectrograms can therefore serve as distinct labels for individual locations, allowing for the identification and recognition of these locations. By adapting an existing acoustic SLAM system (BatSLAM) we have developed a system that demonstrates the feasibility of our proposed method; the results validate the potential of using pulse-echo radar as an exteroceptive sensory modality in topological SLAM systems.**

I. Introduction

Simultaneous localization and mapping (SLAM) is an approach to mapping an unknown environment while at the same time localizing the agent within this generated map, without any prior knowledge about the environment [1], [2]. This is accomplished by gathering information from dedicated sensors by which the robot probes its surroundings and supplying it to a probabilistic algorithm. This can be an (extended) Kalman filter [3] or a particle filter [4], which then processes this information to simultaneously determine the location of the environmental features and the system itself. SLAM is commonly implemented on autonomous vehicles and is mostly employed in GPS-denied environments, highly dynamic surroundings, or situations where the use of external beacon infrastructure is too costly or infeasible.

Most vehicular SLAM systems use dead-reckoning in the form of odometry as a basis for localization. However, this is usually inadequate to perform reliable navigation because wheel slippage, uneven terrain, and measurement inaccuracies introduce errors in the pose estimate which accumulate over the course of the trajectory, causing the estimate to drift away from its actual value [5]. For this reason, odometry is usually combined with one or more additional sensors, allowing the system to achieve a much more accurate result. A wide variety of sensors can be employed to perform SLAM, including ultrasonic distance sensors [1], [6], laser rangefinders [7], optical cameras [8], and ranging cameras [9]. As SLAM begins to pervade the field of robotic localization, its implementations and applications are being pushed to new boundaries. Early solutions were restricted to localization in two dimensions with three degrees of freedom (3DoF), whereas current solutions have evolved to handle 3D localization with 6DoF [10]. Example applications of systems which implement SLAM include robot vacuums [11], unmanned aerial vehicles (UAVs) [12], and the increasingly popular self-driving cars [13].

In this paper we introduce a novel approach to perform SLAM by means of biomimetic radar. Unlike most systems which use radio waves as their principal sensory modality, this approach employs ultra-wideband (UWB) pulse-echo signals instead of the more commonly used frequency-modulated continuous-wave (FMCW) signals [2]. The pulse-echo technique is similar to echolocation as performed by most types of bats, i.e. biological sonar. In robotics, sonar is often considered as a limited, rudimentary method of sensing. However, bats demonstrate otherwise, as can be observed from their maneuverability and navigational skills, which fully rely on ultrasonic echolocation. So-called broadband bats achieve this by making use of temporal and spectral cues present in the echoes which are caused by the filtering effects of their morphology [14].

This functionality was the premise for the development of BatSLAM [15], a biologically inspired system that uses the principle of echolocation and complementary sonar sensors [16], [17] to perform SLAM. By adapting an existing visual SLAM approach to be able to use sonar data as input, BatSLAM shows that ultrasonic pulse-echo signals can contain enough environmental information to successfully perform simultaneous localization and mapping. This is possible because each received echo pattern serves as a distinct label for its corresponding location, allowing the system to identify and recognize the position of the robot. BatSLAM itself is an extension of RatSLAM [18], a direct visual SLAM implementation inspired by the navigational processes present in the hippocampus of rats. The mammalian hippocampus is linked to spatial memory and navigation [19], and by modeling the different types of neurons which correspond to these functions, RatSLAM can perform localization in complex environments using odometry and conventional camera images as input.

The aim of RadarSLAM is to produce the same capabilities as BatSLAM by transferring its principle workings from the acoustic to the electromagnetic domain. Although development is still in an early stage, we have come to a preliminary system which demonstrates the feasibility of this approach. By converting the signals generated by pulse-echo radar measurements to spectrograms, it is possible to produce unique fingerprints of locations in the environment, which can then be used by RatSLAM to successfully map the surroundings and localize the mobile agent within this map. This takes the technique of directly using signal waveforms as labels, as seen in [20], one step further by increasing the use of the information contained in the frequency spectrum of the echo. In addition to our own novel SLAM setup, we execute an existing SLAM system in parallel which serves as ground truth. This system is composed of a lidar sensor and a reliable SLAM algorithm [21] and is used to benchmark our own results.

The main motivation for developing a radar sensor which can be used to perform SLAM is for its use in autonomous navigation. Autonomous vehicles are starting to permeate many aspects of both industrial and consumer domains and are considered one of the most important emerging technologies by the World Economic Forum [22]. SLAM allows such vehicles to work in dynamic or even unknown environments without the need for human operators, potentially making them more safe and efficient. Employing radar as one of the main sensors gives them resilience to various environmental conditions such as rain, fog or smoke, thus further adding to their robustness.

The rest of the paper is structured as follows: Section II gives an overview of both the hardware and software components which the system comprises. Section III takes an in-depth look at the radar sensor, covering both the transceiver and signal processing. In Section IV the overall functionality of the system and its underlying components are explained. Experimental results are presented and discussed in Section V. Lastly, the conclusion on the method and its outcome is drawn in Section VI, which also gives insight into future improvements to the system.

II. SLAM SYSTEM SETUP

This section describes the hardware and software that compose the system, including the ground-truth subsystem, to give a better understanding of its workings and to allow others to reproduce the presented results using their own setup. Currently the system is a prototype used for research. However, there is no major inherent cost or complexity to the components and materials used, thus it is reasonable to assume that it can become more affordable in the future through further developments and large scale manufacturing.

A. Hardware

The system is created in an ad-hoc fashion by mounting the required sensors and computational unit on a mobile robot. This setup allows adding or removing parts as needed.

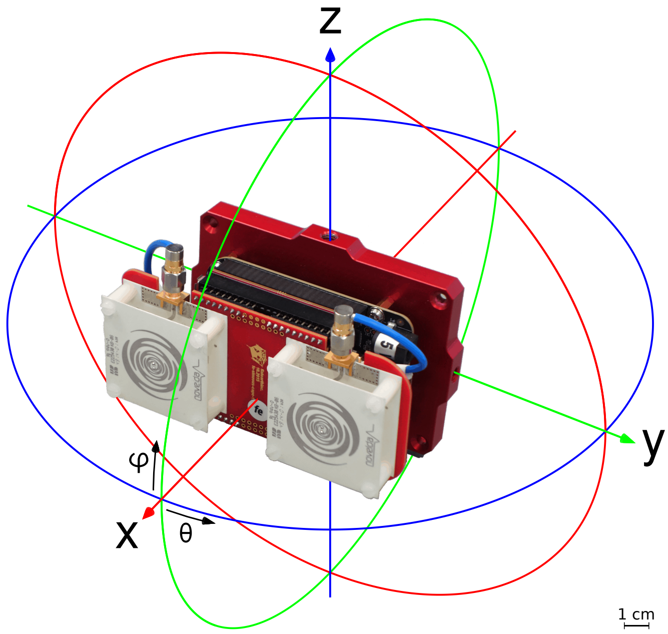

Figure 1. The Salsa Ancho radar development kit, including sinuous antennas, an X2 SoC, a BeagleBone Black, and a mounting plate in descending order of proximity. Spatial axes (x, y, z) and spherical angles (azimuth (θ), elevation (φ)) illustrate the radar's frame of reference.

1) Mobile robot: The basis for the system is the Pioneer P3-DX research mobile robot. It has a differential drive consisting of two separately driven wheels, each featuring rotary encoders which allow for the estimation of their angular motion. This makes it possible to obtain the odometry which is required as input for the SLAM algorithms. It is also possible to directly access the battery of the robot, which is necessary to power the custom peripherals.

2) Computing unit: An Intel NUC 5I7RYH serves as a compact dedicated PC, being only $11 \times 11 \times 5\,\mathrm{cm}$ in size. It features an i7-5557U processor, $16\,\mathrm{GB}$ RAM, SSD storage and has a reasonable peak power consumption of $65\,\mathrm{W}$.

3) Laser rangefinder: As mentioned in Section I, ground truth is required to compare our own result to one which is known to be correct. For this purpose, the sensor used to obtain the measurements is a scanning laser rangefinder (Hokuyo UBG-04LX-F01); it has a range of 20 to $5600\,\mathrm{mm}$, an accuracy of $1\,\%$, and an angular resolution of $0.36°$, allowing it to generate reliable scans of the surrounding area.

4) Radar sensor: The principal sensor of this setup is Flat Earth's Salsa Ancho X2 development kit, which combines a BeagleBone Black with Novelda's Xethru X2 radar system on a chip (SoC) through the use of a custom cape. It also features directional sinuous antennas for both the emitter and receiver, as shown in Figure 1. The sensor has an operating bandwidth of $3\,\mathrm{GHz}$ which is tunable within a frequency range of 4.5 to $9.5\,\mathrm{GHz}$ through the use of 10 separate pulse generators. The chip has a maximum pulse repetition frequency (PRF) of $100\,\mathrm{MHz}$ and a sampling rate of $39\,\mathrm{GS/s}$ (gigasamples per second), which equals a range accuracy of $4\,\mathrm{mm}$ and allows for Nyquist-conform sampling.

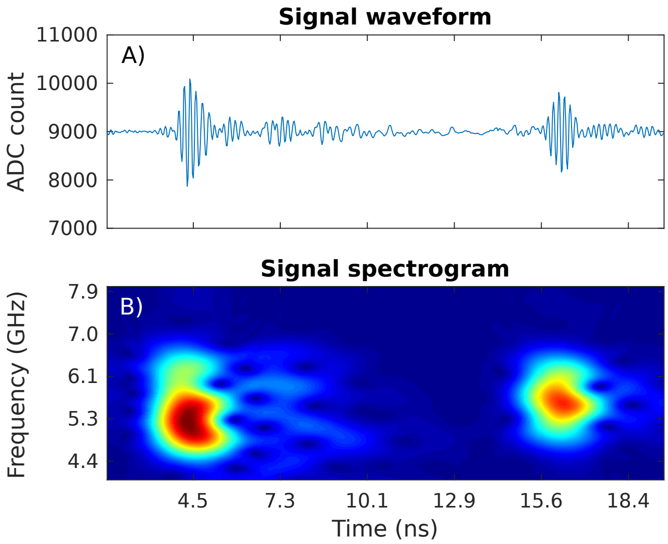

Figure 2. A) Temporal waveform of the recorded radar signal in which two distinct ripples, representing the emitted pulse and received echo, can be seen. B) Corresponding spectrogram of the signal. The two blotches visualize the same emitted pulse and echo not only in time and intensity but also frequency.

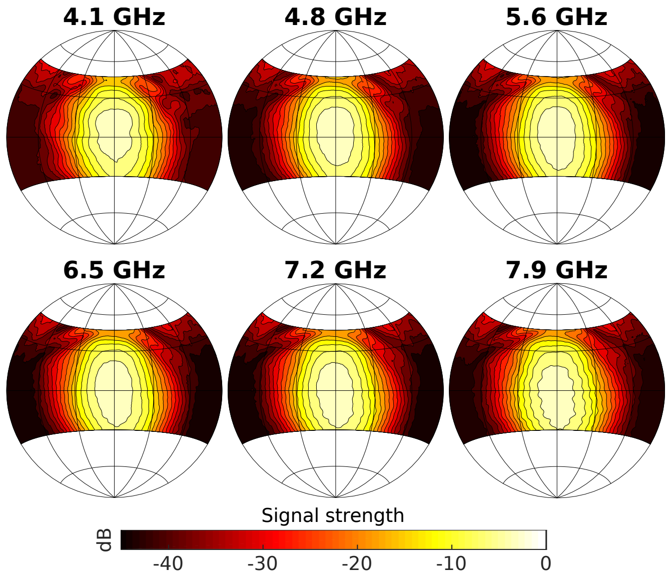

Figure 3. Radiation patterns of the Novelda sinuous antenna, empirically determined using a pan-tilt system and a retroreflector. Measurements were performed for 4.1, 4.8, 5.6, 6.5, 7.2 and 7.9 GHz, and range from $-90°$ to $90°$ in azimuth and $-30°$ to $47°$ in elevation. As can be observed, the antenna exhibits a moderate directionality with almost no variation in the direction of its main lobe.

B. Software

The software of the system is divided into multiple modules which exchange data through use of the Robot Operating System (ROS) framework [23]. ROS serves as middleware for inter-component communication by implementing a publish-subscribe pattern, supporting a heterogeneous network of devices with a high degree of abstraction.

1) ROSARIA: The Advanced Robot Interface for Applications (ARIA) provides an interface to the P3-DX's internal operating system. ROSARIA is a wrapper interface which exposes ARIA to the ROS network, enabling integrated control of the robot's functionality. This includes setting the robot's velocity, retrieving the odometry information, and reading the battery voltage.

2) GMapping & AMCL: The software modules composing the ground-truth setup; GMapping is the ROS implementation of OpenSLAM's GMapping [21] and generates accurate maps based on odometry and laser scan data [24]. Once a map has been created, the adaptive Monte Carlo localization (AMCL) module is used to obtain reliable pose estimates [4]. The produced maps and trajectories can then be used to demonstrate the validity and accuracy of our own experimental results.

3) RadarSLAM: The core of the system, this module is written in MATLAB and controls the radar sensor board through the SalsaLab toolbox, performs signal processing on the received echoes and interfaces with the OpenRatSLAM MATLAB implementation [25], [26]. Additionally, it is also connected to the ROS network by means of the Robotics System Toolbox to obtain odometry information from the P3DX robot and pose estimates from the AMCL module.

III. Radar Sensor

It is because of recent developments in radar technology that we are able to present the system described in this paper. The X2 SoC is one of the first commercially available sensors which allows for the full wave reconstruction of received echo signals because its sampling rate (39 GS/s) is well above $2\times$ the signal frequency (10 GHz), fulfilling the Nyquist criterion. This is a necessity because it enables us to convert the received echo signals into their time-frequency representations, i.e. spectrograms, using the short-time Fourier transform. These spectrograms are fundamental to our application: emitted signals interact differently with the environment at each location by means of reflection, absorption, scattering, etc. causing multiple echoes that exhibit time-delays, attenuation, and mutual interference. A spectrogram captures all these spatiospectral features and can therefore serve as a unique fingerprint by which a location can be identified and recognized. An exemplary pulse-echo signal and its corresponding spectrogram is shown in Figure 2.

An important feature which contributes to this functionality is the ultra-wideband aspect of the sensor. Due to the capability of emitting UWB signals, the received echoes exhibit increased salience from which additional information about the environment can be extracted; individual frequencies interact differently with environmental features causing distinct alterations to the echoes, which adds to their uniqueness and thus allows for better differentiation. To exploit this effect even further, we perform three consecutive UWB pulse-echo measurements at each location, using separate pulse generators with center frequencies at 6.4 GHz, 7.3 GHz, and 7.8 GHz.

Another property that significantly influences the salience

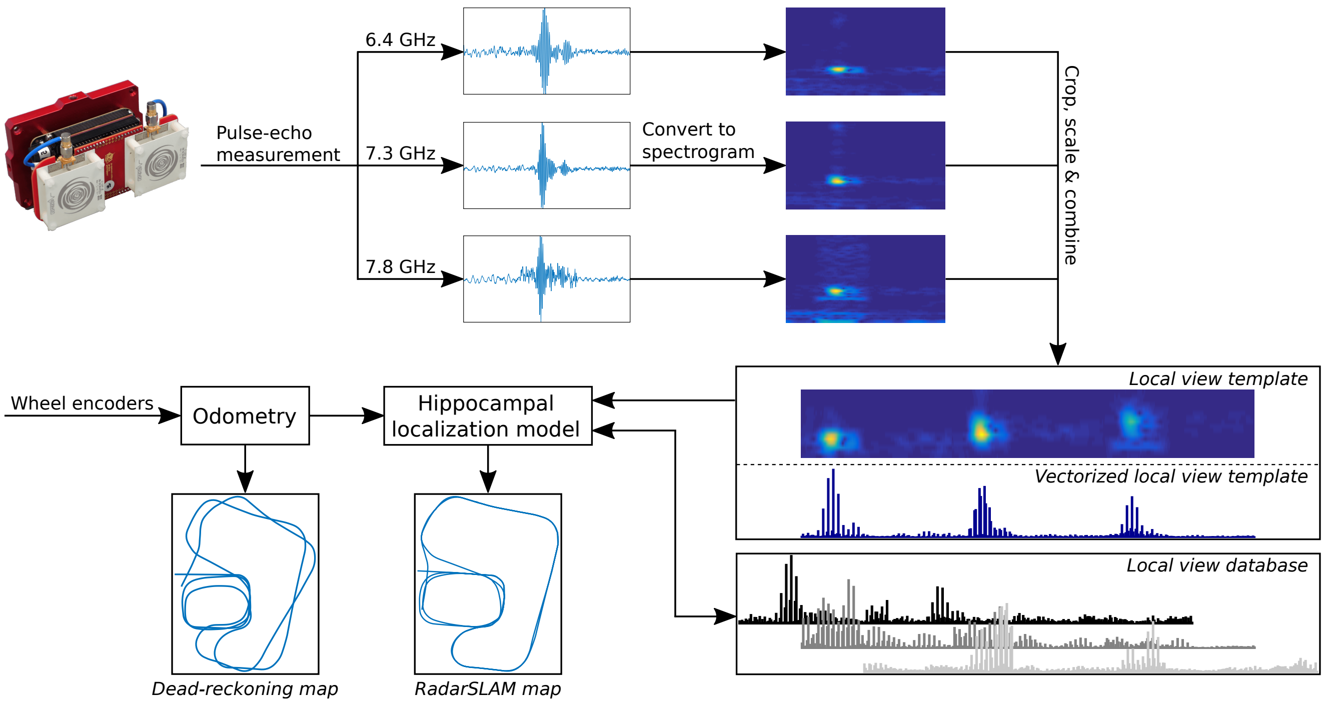

Figure 4. Schematic representation of the workings of RadarSLAM. Starting top-left, pulse-echo radar measurements are acquired at multiple center frequencies. The waveform signals are converted to spectrograms and further modified to form a local view template. Next, this template is fed into the RatSLAM hippocampal model together with the odometry gathered from the wheel encoders. RatSLAM then tries to identify a match for the template in its database. If one is found it will either confirm the current pose estimate or indicate a possible miscalculation. If enough evidence of a positional discrepancy is observed, the pose estimate is corrected and the map adjusted accordingly.

of environmental features is the directivity pattern of both the transmitting and the receiving antenna. Ideally the sensor would scan the environment, giving information about both distance and direction of reflectors. This would produce a very explicit descriptor of each location, making it easy to distinguish between them and thus facilitating localization. Besides by a rotating antenna or phased array, scanning can be accomplished by a frequency-scanning antenna of which the direction of the main lobe(s) changes according to the frequency of the emitted or received signal. An exemplary implementation of such an antenna can be found in [27] and [28]. There are multiple reasons for using this type of antenna instead of the alternatives; mechanical scanning, as present in lidar sensors for example, requires moving parts driven by motors, which increase the complexity and weight of the system, and can also generate gyroscopic forces that could be undesirable on vehicles such as drones. Electronically scanned arrays, i.e. phased arrays, on the other hand are composed of up to thousands of individual antennas, which again raises the complexity and adds to its size, weight, and cost. Although frequency-scanning antennas have reduced accuracy compared to these alternatives, they offer an inherently low complexity of their components [16]. Additionally, processing of the directionality of a signal occurs in the analog domain, which reduces the requirement for computational power.

Currently, we are using the standard antennas supplied with the Salsa Ancho development kit. These are directional sinuous antennas with a reported opening angle of $65°$ in azimuth and $85°$ in elevation, and frequency range of 6.0 to 8.5 GHz with a typical gain of 6.0 dBi [29]. As illustrated in Figure 3, these antennas are moderately directional and do not exhibit any notable variation in their radiation pattern. Consequently, they embed little to none information about the location of reflectors in the signal through modulation of the spatiospectral characteristics and thus are not optimal for our needs. Regardless, the system can still successfully perform SLAM using them, as is shown in Section V, and we presume performance will increase considerably when utilizing specialized custom antennas.

A last aspect of the sensor which adds to the overall functionality of the system is its frequency range, which covers the radar C-band and lower part of the X-band (IEEE radar-frequency band designations). These frequencies are reflected by most materials which are common in man-made structures and objects, such as brick and concrete, metal, glass, and wood to a lesser extent. Opposed to lidar, which uses electromagnetic frequencies near the visible spectrum, these radar frequencies are not strongly hampered by airborne particles such as smoke, rain, and dust, or by temperature and pressure, which is useful in a variety of circumstances; a radar sensor can ensure that an autonomous vehicle remains functional even when exposed to adverse environmental conditions, adding to its operational safety and efficiency. Examples include navigating in low-visibility weather, or firefighters sending an exploration robot into a burning building, filled with smoke and hot air, to map the internal structure [30].

IV. RadarSLAM

RadarSLAM is in effect an adaptation of a preexisting SLAM system, namely BatSLAM, which in itself is an adaptation of RatSLAM. To fully understand the workings of RadarSLAM it is necessary to have an insight in the workings of these two systems as well.

A. RatSLAM

RatSLAM is a vision based SLAM implementation inspired by the navigational processes which occur in the hippocampal regions of a rat's brain. It models certain types of cells, i.e. neurons, to achieve its mapping and localization functionality; in biology, positional information is represented by *place cells* [31], which activate at specific locations due to estimation of self-motion or recognition of visual scenes, and *head direction cells* [32], which activate when facing in a specific absolute direction. In RatSLAM these two cells are combined into a single digital counterpart, *pose cells (PC)* [33], which encode both location and orientation. Visual recognition is delegated to *local view cells (LV)*, which are associated with distinct visual scenes and become active when their corresponding *local view template* is observed. In the case or RatSLAM, self-motion information takes the form of odometry, while observations of visual scenes are represented by digital camera images.

Experiences link pose cells and local views cells together, storing at which location each visual scene was observed, as well as the positional relationship between these locations, which is represented by the *experience map*. Additionally, pose cells and local views cells are connected by a continuous attractor network (CAN) [34]; shortly summarized, this is a network of neurons with excitatory and inhibitory interconnections in which activity is injected by external stimuli, after which it converges to a stable pattern representing a specific outcome.

Because the experience map is actually a graph in which locations are represented by nodes, it is not strictly metric by nature, but instead it is topological. A metric map has a direct geometrical correlation with the physical world, whereas a topological map only retains adjacency of locations but does not inherently depict distance or absolute direction correctly. However, because RatSLAM takes odometry as input, it can adequately estimate the positional relation between experiences and so the output still resembles a metric map. It is worth to note that because SLAM only uses on-board sensors, the obtained positions are always relative to a local reference frame, instead of absolute in a global reference frame as is the case in solutions which use external beacon infrastructure.

Unlike most visual SLAM systems, RatSLAM takes a direct approach instead of the more common feature-based approach. In the latter, each incoming image is analyzed to detect and extract visually salient features which act as descriptors for the image and thus for the position at which it was taken [35]. Such features include edges, corners and regions of similar appearance. A direct visual approach on the other hand does not perform any interpretation on the image, but instead uses the image in its entirety to serve as a descriptor for the location, where each pixel counts as an individual feature [36]. This makes a direct approach more robust to situations where conventional features are scarce, and has the additional advantage that it can make use of images that do not originate from optical cameras and thus do not necessarily contain any visual salience in the classical sense. This last property permits RatSLAM to be used for a wide variety of applications with diverse types of input. Non-visual sensory modalities that have been used in combination with RatSLAM include Wi-Fi signals [37], sense of touch [38], and in-air ultrasonic waves [15], the latter of which will be detailed in Section IV-B.

B. BatSLAM

As mentioned before, BatSLAM is a SLAM system which uses ultrasonic echolocation, i.e. sonar, to perform its place recognition. It does this by emitting an ultrasonic hyperbolic chirp which ranges from 20 to $100\,\mathrm{kHz}$ and then recording the resulting echoes, which are received by two separate microphones encased in plastic replicas of bat pinnae. Because these echoes are created by complex interactions with structures and objects in the environment, they are well suited to serve as unique descriptors for locations. The goal of the plastic pinnae is, just as their biological counterparts, to introduce even more environmental information in the echoes by filtering frequencies according to their angle of incidence [14], which adds cues about the location of reflectors. Furthermore, the use of two microphones introduces additional cues because an incident echo coming from a certain direction might arrive at a different time and with a different intensity at each microphone, giving rise to interaural timing and intensity differences which have been shown to be of great importance in spatial hearing [39]. This is further enhanced by the fact that the pinnae enclosing the microphones are pointed in opposite directions. By converting the received echo signals to spectrograms, it becomes possible to make use of both this temporal and spectral information which is embedded in them.

In BatSLAM, the spectrograms generated from each microphone signal are concatenated to form a single image, which is further subsampled and smoothed to serve as a local view template. By tweaking the CAN parameters and implementing a custom comparison algorithm which can determine the similarity between these local views, the system is then able to perform SLAM by means of echolocation.

C. RadarSLAM

Using the expertise gained from BatSLAM, the goal of RadarSLAM is to transfer the principles of sonar to the domain of radar. In addition to the advantages of radar mentioned in Section III, there are several others associated with using it instead of sonar. Firstly, its signal travels at the speed of light rather than the speed of sound and can therefore cover distances more rapidly, which causes echoes to return faster, resulting in a much higher PRF. Secondly, ultrasonic sound waves attenuate at around $1\,\mathrm{dB/m}$ due to atmospheric effects,

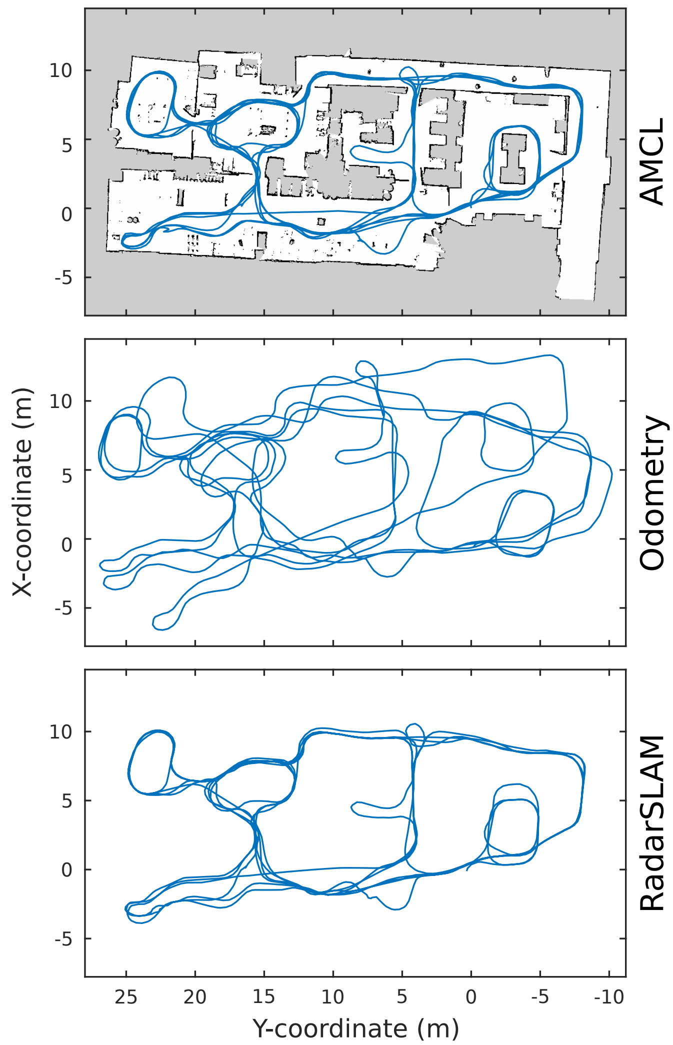

Figure 5. Comparison of the results obtained from a single run in an industrial lab setting. Top: ground-truth trajectory generated by the AMCL module based on laser rangefinder scans. Middle: odometry trajectory generated by dead-reckoning based on rotary encoder readings. Bottom: experience map generated by RadarSLAM based on the combination of odometry with pulse-echo radar measurements.

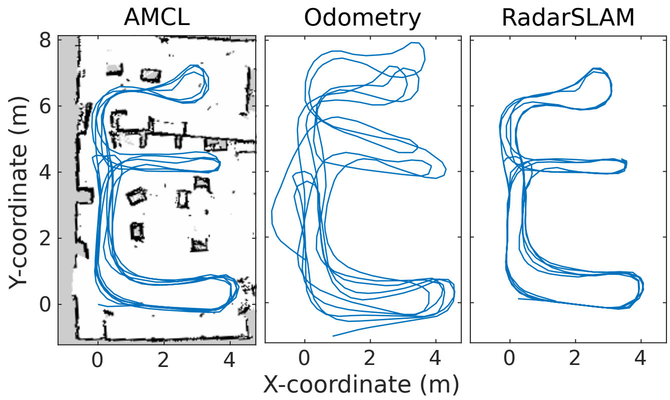

Figure 6. Instance of a run performed in an office environment. Left: ground-truth trajectory. Middle: odometry trajectory. Right: experience map. The same definitions apply as in Figure 5.

Table I
METRICS PERTAINING TO THE TRAJECTORY SHOWN IN FIGURE 5.

Total distance traveled	599.8 m
Average speed	0.5 m/s
Number of sampled locations	1730
Cumulative odometry error	3441.9 m
Cumulative RadarSLAM error	749.3 m
Average odometry error	1.99 m
Average RadarSLAM error	0.43 m
Maximum odometry error	4.82 m
Maximum RadarSLAM error	1.36 m

whereas electromagnetic waves only attenuate in the order of $0.01\,\mathrm{dB/km}$ at the frequencies used, which results in stronger echoes and a higher signal to noise ratio. Lastly, radar is not as greatly affected by air conditions such as temperature, humidity and pressure as sonar, making it more viable in a wider range of situations.

A full overview of the workings of RadarSLAM is given in Figure 4. Shown in the top left, the radar sensor is used to obtain three consecutive pulse-echo readings at 6.4, 7.3 and 7.8 GHz for a single position. Each of these echo waveforms is converted to a spectrogram, which are then cropped to a fixed time and frequency range that is of interest to our application. These separate frames are combined into a single image which serves as the local view template for that specific position. Each cycle of the algorithm, the current local view template is fed into the hippocampal model of RatSLAM which retains a database of all previously perceived local views. This template is then compared to the entries in the database to determine a match, using the same method as described in [15]. If one is found, the local view cell which corresponds to the matched template is activated, else a new local view cell is created for this template and added to the database. This local view cell will in turn activate its associated pose cell. In the case that this is the pose cell which already represents the system's current pose estimate, it will be reinforced. Else, the system will enter a state in which multiple possibilities are maintained. If the observed visual evidence causes another pose cell to dominate the network activity, this cell will represent the system's new pose estimate from then on and a loop closure will occur; the robot's position is updated and the map adjusts for the error in the trajectory through graph relaxation. This results in a more exact localization of the robot and a map which is more accurate.

V. EXPERIMENTAL RESULTS

The validity and accuracy of the system were determined by performing multiple mappings of a feature-rich environment, in this case an industrial lab. The results exhibit a notable improvement over the use of odometry by itself, as shown in Figure 5. It can clearly be observed that the map produced by RadarSLAM has a higher similarity to the ground truth than the map generated solely based on odometry. Additional metrics for the trajectory, presented in Table I, support this observation, showing that RadarSLAM outperforms odometry by a factor of 4. The cumulative, average and maximum distance

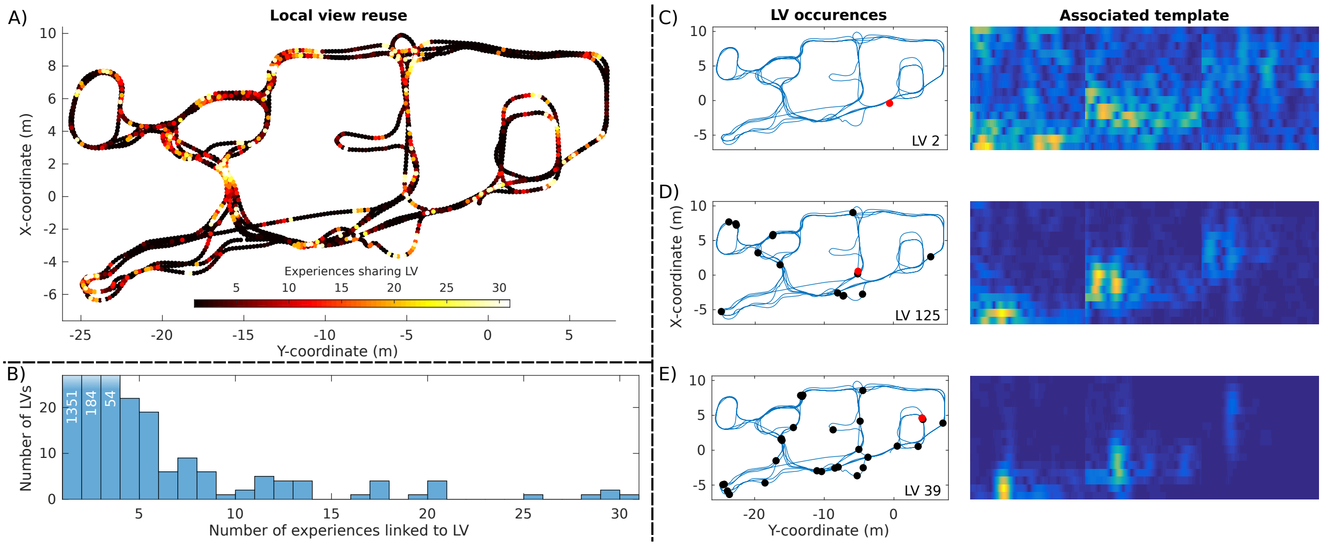

Figure 7. A) Map indicating the reuse of local views. Each experience is colored according to the amount of other experiences that share its local view. B) Histogram showing the coupling between experiences and local views. Each bar indicates the amount of local views that have a particular number of experiences linked to them. C-E) Examples of local views, showing by which experiences they are used and where these are located. The red dot indicates the first occurrence, black dots indicate subsequent occurrences. LV 2 is used by a single experience, LV 13 is shared by 16 experiences, and LV 39 is shared by 31 experiences

error between the resulting trajectories and the ground truth are determined by first aligning the trajectories using a rigid iterative closest point (ICP) algorithm and then calculating the pointwise euclidean distance between each corresponding location. Six additional runs of varying lengths were completed in the same environment and produced comparable results. Furthermore, the system was also tested in a smaller-scale office environment where a similar degree of performance was achieved, as can be seen in Figure 6. It should be noted that these results concern comparisons between metric and topological maps, which one should take into account when interpreting them.

Further analysis of the system is shown in Figure 7, which deals with the information content and ambiguity of the local view templates created from the radar measurements. Figure 7A shows a map illustrating the measure in which templates are shared between experiences. This can occur both because repeatedly visited locations are recognized or because separate locations are very similar to each other in terms of their radar echo. Sharing of local view templates between separate locations is not a problem as long as these are singular events and the locations at which it occurs are spatially detached. However, it can become a problem if this is not the case; if sequences of measurements taken at different locations appear alike and are incorrectly identified as such, this results in false-positive positional matches and erroneous loop closures. To achieve optimal performance, a balance must be found; too much sharing means templates contain a high amount of ambiguity and thus do not represent their associated position conclusively, whereas too little sharing means that the templates have a very high uniqueness, causing any noise or deviation in position to hinder a correct match.

The same concept is illustrated in Figure 7B, where it can be seen that 80 % of local view templates are linked to a distinct experience, while the remaining 20 % are being shared between experiences, with fewer occurrences as sharing increases. Samples of such templates are shown in Figure 7C-E, where we haven taken those with the least, mean, and maximum amount of sharing respectively. As can be observed, the template for LV 2 is very distinct with many features plus some added noise and thus only perceived at a single location, whereas LV 39 does not contain a lot remarkable elements such as multiple echoes or frequency cues, which seems to be a common occurrence for quite a number of locations.

VI. Conclusion & Future Work

This paper presents a prototype for a novel approach to perform SLAM using radar. The system's workings and advantages have been explained and the feasibility of the employed technique has been validated using experimental results. As far as the authors of this paper know, no other systems use radar in a direct SLAM approach by converting the electromagnetic signal waveforms to spectrograms.

Using BatSLAM as a basis while moving from the acoustic to the electromagnetic domain, we have demonstrated that UWB pulse-echo radar, without feature detection or interpretation, can be successfully used as a primary sensory modality to uniquely identify and recognize distinct locations, allowing SLAM to be performed. This is possible even though only a single sensor without a specialized antenna is used, which allows room for improvement of the information content of the local view templates (as established for acoustic sensing in [40]) and thus warrants further exploration of the approach.

In future research, we plan on employing dual radar sensors with custom antennas, which will introduce both new binaural cues in the form of interaural differences and additional monaural cues in the form of spatiospectral cues in the echoes. This increases the amount of contained information and thus allow for better localization. This improved system is to be tested in more varying environments and conditions to fully determine its capabilities. Furthermore, we intend to insert artificial drift in the odometry to establish the limit of error RadarSLAM can compensate for. An additional long-term goal is to extend the system to 3D/6-DoF SLAM which will allow for its use on aerial vehicles such as drones.

VII. Acknowledgements

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References

[1] J. J. Leonard and H. F. Durrant-Whyte, "Simultaneous map building and localization for an autonomous mobile robot," in *Intelligent Robots and Systems '91. 'Intelligence for Mechanical Systems, Proceedings IROS '91. IEEE/RSJ International Workshop on*, vol. 3, 1991.

[2] M. W. M. Gamini Dissanayake, P. Newman, S. Clark, H. F. Durrant-Whyte, and M. Csorba, "A solution to the simultaneous localization and map building (SLAM) problem," *IEEE Transactions on Robotics and Automation*, vol. 17, no. 3, 2001.

[3] R. Smith, M. Self, and P. Cheeseman, "Estimating Uncertain Spatial Relationships in Robotics," *Autonomous Robot Vehicles*, vol. 4, 1990.

[4] S. Thrun, D. Fox, W. Burgard, and F. Dellaert, "Robust Monte Carlo localization for mobile robots," *Artificial Intelligence*, vol. 128, 2001.

[5] J. Borenstein and L. Feng, "Measurement and Correction of Systematic Odometry Errors in Mobile Robots," *Ieee Transactions on Robotics and Automation*, vol. 12, no. 6, 1996.

[6] J. Steckel and H. Peremans, "Spatial sampling strategy for a 3D sonar sensor supporting BatSLAM," *IEEE International Conference on Intelligent Robots and Systems*, vol. 2015-Decem, 2015.

[7] M. Bosse and R. Zlot, "Keypoint design and evaluation for place recognition in 2D lidar maps," *Robotics and Autonomous Systems*, vol. 57, no. 12, 2009.

[8] A. J. Davison, I. D. Reid, N. D. Molton, and O. Stasse, "MonoSLAM: Real-time single camera SLAM," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 6, 2007.

[9] P. Henry, M. Krainin, E. Herbst, X. Ren, and D. Fox, "RGB-D Mapping : Using Depth Cameras for Dense 3D Modeling of Indoor Environments," in *In RGB-D: Advanced Reasoning with Depth Cameras Workshop in conjunction with RSS*, vol. 1, no. c, 2010.

[10] M. Bibuli, M. Caccia, and L. Lapierre, "6D SLAM - 3D Mapping Outdoor Environments," *IFAC Proceedings Volumes*, vol. 7, no. 1, 2007.

[11] Neato XV-11. Neato Robotics. [Online]. Available: https://www.neatorobotics.com/robot-vacuum/xv/xv-11/

[12] J. Artieda, J. M. Sebastian, P. Campoy, J. F. Correa, I. F. Mondragón, C. Martínez, and M. Olivares, "Visual 3-D SLAM from UAVs," *Journal of Intelligent and Robotic Systems: Theory and Applications*, vol. 55, no. 4-5, 2009.

[13] E. Guizzo, "How Google's self-driving car works," *IEEE Spectrum Online*, vol. 18, 2011.

[14] J. Reijniers, D. Vanderelst, and H. Peremans, "Morphology-induced information transfer in bat sonar," *Physical Review Letters*, vol. 105, no. 14, 2010.

[15] J. Steckel and H. Peremans, "BatSLAM: Simultaneous Localization and Mapping Using Biomimetic Sonar," *PLoS ONE*, vol. 8, no. 1, 2013.

[16] J. Steckel, F. Schillebeeckx, and H. Peremans, "Biomimetic sonar, outer ears versus arrays," *Proceedings of IEEE Sensors*, 2011.

[17] J. Steckel, A. Boen, and H. Peremans, "Broadband 3-D sonar system using a sparse array for indoor navigation," *IEEE Transactions on Robotics*, vol. 29, no. 1, 2013.

[18] M. J. Milford, G. F. Wyeth, and D. Prasser, "RatSLAM: A Hippocampal Model for Simultaneous Localization and Mapping," *Proceeding of the 2004 IEEE international Conference on Robotics & Automation*, 2004.

[19] T. Hafting, M. Fyhn, S. Molden, M.-B. Moser, and E. I. Moser, "Microstructure of a spatial map in the entorhinal cortex," *Nature*, vol. 436, no. 7052, 2005.

[20] A. E. Eijiro Takeuchi and J. Roberts, "Localization and Place Recognition Using an Ultra-Wide Band (UWB) Radar," *Field and Service Robotics*, 2013.

[21] G. Grisetti, C. Stachniss, and W. Burgard, "Improved techniques for grid mapping with Rao-Blackwellized particle filters," *IEEE Transactions on Robotics*, vol. 23, no. 1, pp. 34–46, 2007.

[22] The World Economic Forum's Meta-Council on Emerging Technologies, "Top 10 Emerging Technologies of 2016," World Economic Forum, Geneva, Tech. Rep., 2016.

[23] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, E. Berger, R. Wheeler, and A. Mg, "ROS: an open-source Robot Operating System," *Icra*, vol. 3, no. 1, 2009.

[24] J. M. Santos, D. Portugal, and R. P. Rocha, "An evaluation of 2D SLAM techniques available in Robot Operating System," *2013 IEEE International Symposium on Safety, Security, and Rescue Robotics, SSRR 2013*, 2013.

[25] D. Ball, S. Heath, M. Milford, G. Wyeth, and J. Wiles, "A Navigating Rat Animat," *Proceedings of the 12th International Conference on the Synthesis and Simulation of Living Systems*, vol. 40, no. 3, 2010.

[26] D. Ball, S. Heath, J. Wiles, G. Wyeth, P. Corke, and M. Milford, "OpenRatSLAM: An open source brain-based SLAM system," *Autonomous Robots*, vol. 34, no. 3, 2013.

[27] S. T. Yang and H. Ling, "Design of a microstrip leaky-wave antenna for two-dimensional bearing tracking," *IEEE Antennas and Wireless Propagation Letters*, vol. 10, 2011.

[28] Y. B. Li, X. Wan, B. G. Cai, Q. Cheng, and T. J. Cui, "Frequency-controls of electromagnetic multi-beam scanning by metasurfaces." *Scientific reports*, vol. 4, 2014.

[29] *Sinuous Antenna Data Sheet*, Novelda, 2011, rev. 0.1.

[30] J. W. Starr and B. Y. Lattimer, "Evaluation of Navigation Sensors in Fire Smoke Environments," *Fire Technology*, vol. 50, no. 6, 2014.

[31] J. O'Keefe, "Place units in the hippocampus of the freely moving rat," *Experimental Neurology*, vol. 51, no. 1, 1976.

[32] J. S. Taube, "Head direction cells and the neurophysiological basis for a sense of direction," *Progress in Neurobiology*, vol. 55, no. 3, 1998.

[33] M. Milford and G. Wyeth, "Hippocampal models for simultaneous localisation and mapping on an autonomous robot," in *Australasian Conference on Robotics and Automation*. Australian Robotics and Automation Association Inc, 2003.

[34] a. Samsonovich and B. L. McNaughton, "Path integration and cognitive mapping in a continuous attractor neural network model." *The Journal of neuroscience : the official journal of the Society for Neuroscience*, vol. 17, no. 15, 1997.

[35] A. J. Davison, "Real-time Simultaneous Localisation and Mapping with a Single Camera," *Iccv*, vol. 2, 2003.

[36] G. Silveira, E. Malis, and P. Rives, "An efficient direct approach to visual SLAM," *IEEE Transactions on Robotics*, vol. 24, no. 5, 2008.

[37] R. Berkvens, A. Jacobson, M. Milford, H. Peremans, and M. Weyn, "Biologically inspired SLAM using Wi-Fi," *IEEE International Conference on Intelligent Robots and Systems*, 2014.

[38] M. Salman and M. J. Pearson, "Advancing whisker based navigation through the implementation of Bio-Inspired whisking strategies," in *2016 IEEE International Conference on Robotics and Biomimetics (ROBIO)*. IEEE, 2016.

[39] J. Blauert, *Spatial hearing: the psychophysics of human sound localization*. MIT press, 1997.

[40] J. Steckel and H. Peremans, "Biomimetic sonar for biomimetic SLAM," *Proceedings of IEEE Sensors*, 2012.